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TARGET DETECTION IN GAUSSIAN NOISE USING ARTIFICIAL NEURAL SYSTEMS

BY JEFFREY L. SOLKA GEORGE ROGERS
STRATEGIC SYSTEMS DEPARTMENT

JUNE 1990

NAVAL SURFACE WARFARE CENTER
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FOREWORD

Radar signal processing with multilayered perceptrons was investigated. Networks with no hidden layer and a single hidden layer were tested on field collected millimeter wave target returns which had been corrupted with artificial Gaussian noise at a signal to noise level of 3 dB. Performance as a function of network architecture was characterized.

The authors would like to thank Jim Queen and Karl Krueger for providing the data used in the study and for helpful suggestions concerning data pre-processing.

This study has been supported by the Office of Naval Technology through the Independent Exploratory Development Program and was conducted in the Space and Ocean Geodesy Branch of the Strategic Systems Department.

This technical report has been reviewed by Patrick E. Beveridge, Head of the Space and Ocean Geodesy Branch, and J. Ralph Fallin, Head of the Space and Surface Systems Division.

Approved by:

R. L. Schmidt

R. L. SCHMIDT, Head
Strategic Systems Department

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OVERVIEW

In April of 1988 work was begun at the Space and Surface Systems Division of the Strategic Systems Department at the Naval Surface Warfare Center in Dahlgren, Virginia on applying Artificial Neural Systems (ANS) to radar signal processing. This work was funded as part of the Independent Exploratory Development research program. This report summarizes the current status of this effort as of October 1988.

In identifying a candidate neural network for radar signal processing, many different neural network algorithms, paradigms, were considered. Multilayered Perceptrons (MLPs) and Carpenter Grossberg networks were chosen as the initial paradigms to be investigated. Ease of implementation lead us to employ the MLP algorithm first.

NETWORK TRAINING

The MLPs used for the study contained an input layer, a single hidden or no hidden layer, and an output layer. The input patterns were propogated through the network using the standard equations, and a sigmoid transfer function.[2] For the purposes of this study, no direct links from the input to the output layer were allowed.

Next the edge weight corrections were computed. The two methods which were used in the study for this purpose are the standard error back propagation scheme,[2] and error back propagation with selective learning.[1] The selective learning algorithm was developed in response to certain pathological situations which can occur when using the standard gradient descent algorithm. This procedure is helpful in situations where certain patterns in the training set are sparsely represented, or when certain output states of the network lie

in close error space proximity to the desired output state. A brief description of the algorithm is given below.

On the first pass through the training patterns selective learning does not take place. This pass serves to provide the user with values of rmax and rms. On subsequent passes the following procedure is used to modify the errors of the output nodes.

$$\begin{aligned}&\text{if } (|\delta_j| < \text{mfac} * \text{rms}) \text{ then}\\&\quad \delta_j = \text{efac} * \delta_j \\&\text{endif}\end{aligned} \tag{1}$$

Efac is chosen to lie between 0 and 1, and mfac is chosen to be slightly less than rmax/rms. The rest of the training procedure proceeds as before. A more complete discussion of selected learning is provided elsewhere.[1]

APPROACH

In early 1987 radar data was collected at the Kiernan Reentry Measurement Site (KREMS) at Kawajaleen Atoll in the Marshall Islands, on several objects under various conditions. Millimeter wave radar returns which were collected from a towed kite were used for this study.

Figure 1 illustrates the organization of the data into blocks consisting of 80 amplitude and phase values for both the pp, and the op channels. Two hundred of these pure signal blocks were used to create the training sets. The pre-processing steps for the data are flow charted in Figure 2. Each data pair was transformed to the I Q plane, corrupted with noise, and fast fourier transformed. Pre-processing of the radar data was performed on a Cyber 875.

For each signal plus noise block, a pure noise block was generated as follows. Since the pp channel dominated the signal, a decision was made to use its maximum average power level in the generation of both the noise to be added to both signal channels and the pure noise signal. First, the average power value over all eight pulses was computed for each range bin in the pp channel

$$\bar{P}_i = \frac{\sum_{j=1}^{8} (I^2_{ij} + Q_{ij}^2)}{8} \tag{2}$$

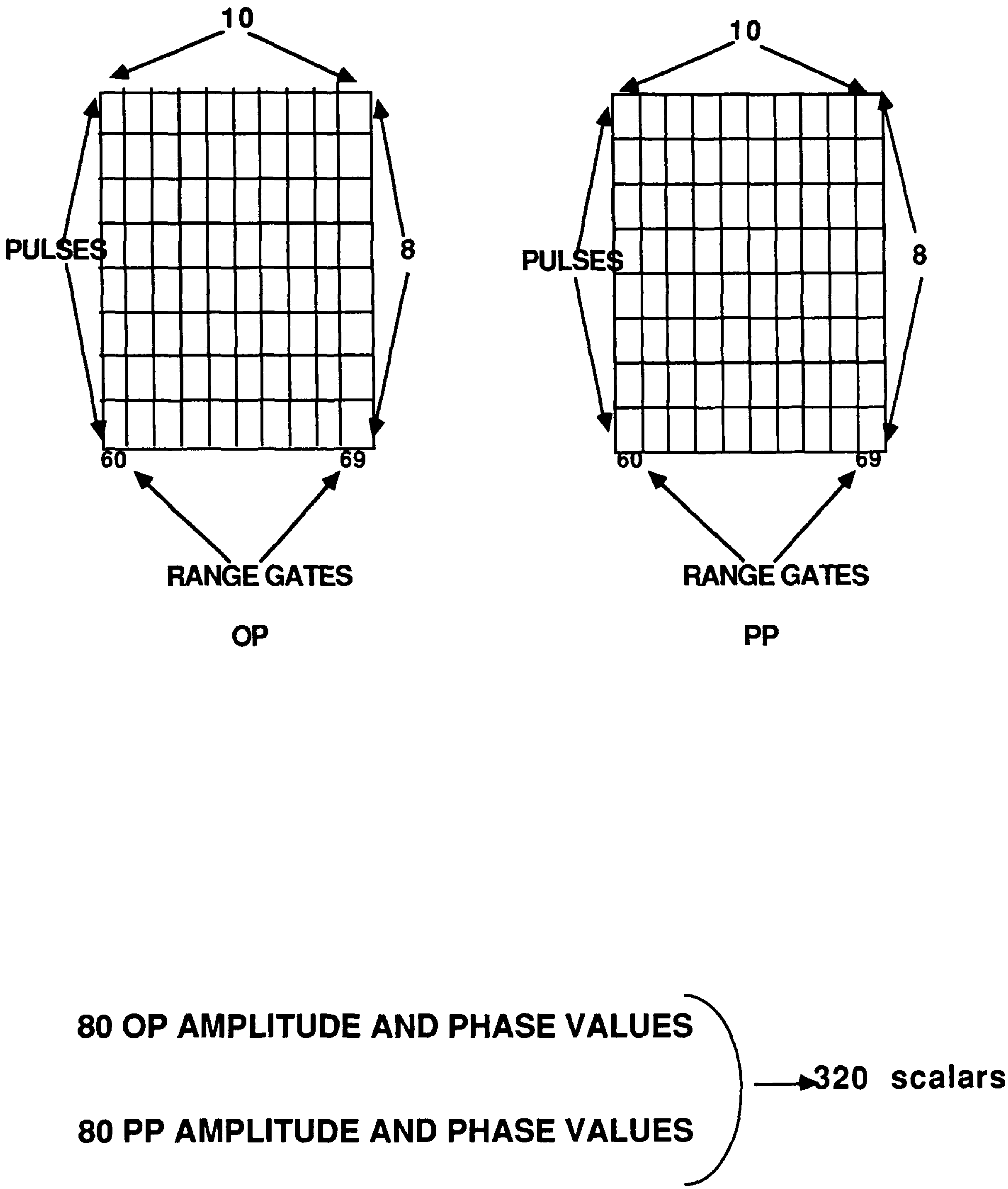

FIGURE 1. DATA BLOCK STRUCTURE

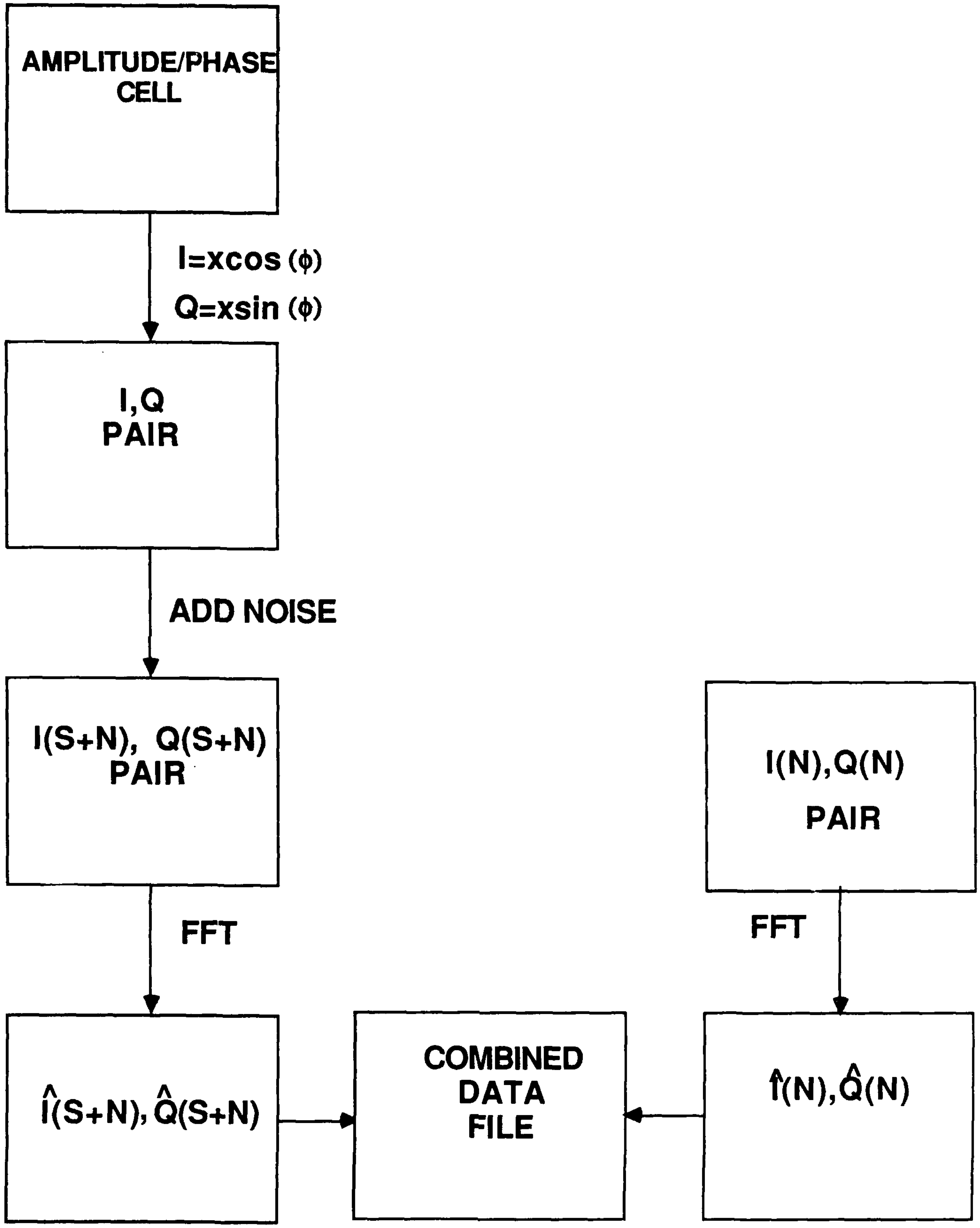

FIGURE 2. DATA PRE-PROCESSING

Next the maximum of these averages was computed

$$\bar{p}_{max} = \max(\bar{p}_1, \bar{p}_2, \bar{p}_3, \ldots, \bar{p}_{10}) \tag{3}$$

Next the user specified signal to noise ratio in decibels was converted to volts^2 ratios

$$sn = 10^{\frac{sndb}{10}} \tag{4}$$

Assuming an equal distribution in both I and Q the rms for the target signal was computed

$$\sigma_{tar} = \sqrt{\frac{\bar{p}_{max}}{2}} \tag{5}$$

Using the user specified signal to noise ratio an rms value was computed for the noise

$$\sigma_{noise} = \frac{\sigma_{tar}}{\sqrt{sn}} \tag{6}$$

Finally 320 Gaussian variants with a mean of 0 and a rms of σ_{noise} were generated to corrupt the target block and a similar number with a mean of 0 and a rms of σ_{noise} became the pure noise block.

Before training could begin the data was normalized to lie between 0 and 1. Initially the 160 $I^2 + Q^2$ values from a given block were normalized by dividing each of them by the largest $I^2 + Q^2$ value in the block. 200 blocks of signal in the presence of noise were placed in a training file with 200 blocks of pure noise. Their alternating placement in the file is illustrated in Figure 3 and an example normalized signal plus noise block is shown in Figure 4.

Various multilayered perceptrons were trained on four files of data at a fixed signal-to-noise ratio. After training the network to a desired rms error level their performance was tested on 10 files of data. This procedure is summarized in Figure 5.

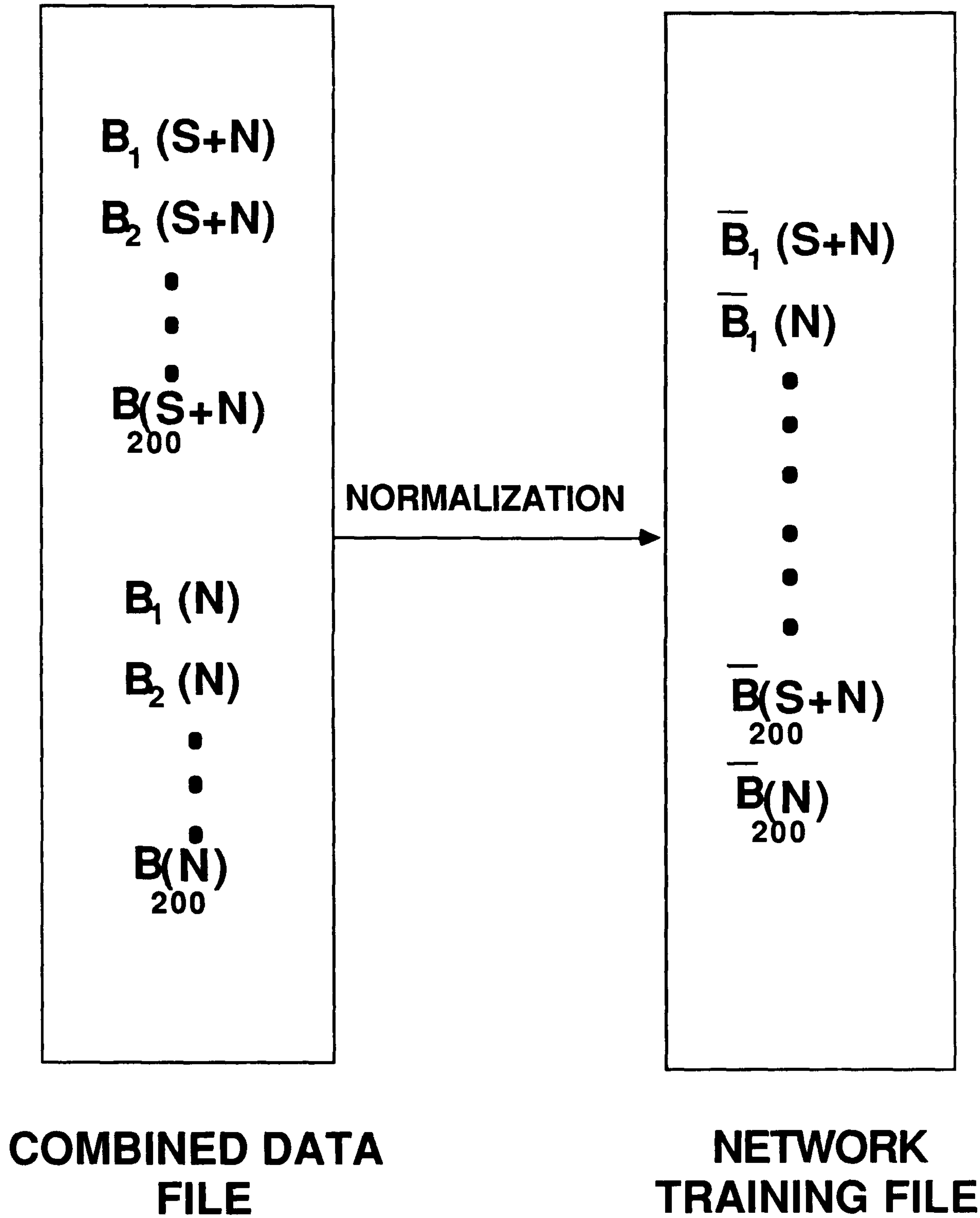

FIGURE 3. TRAINING FILE CREATION

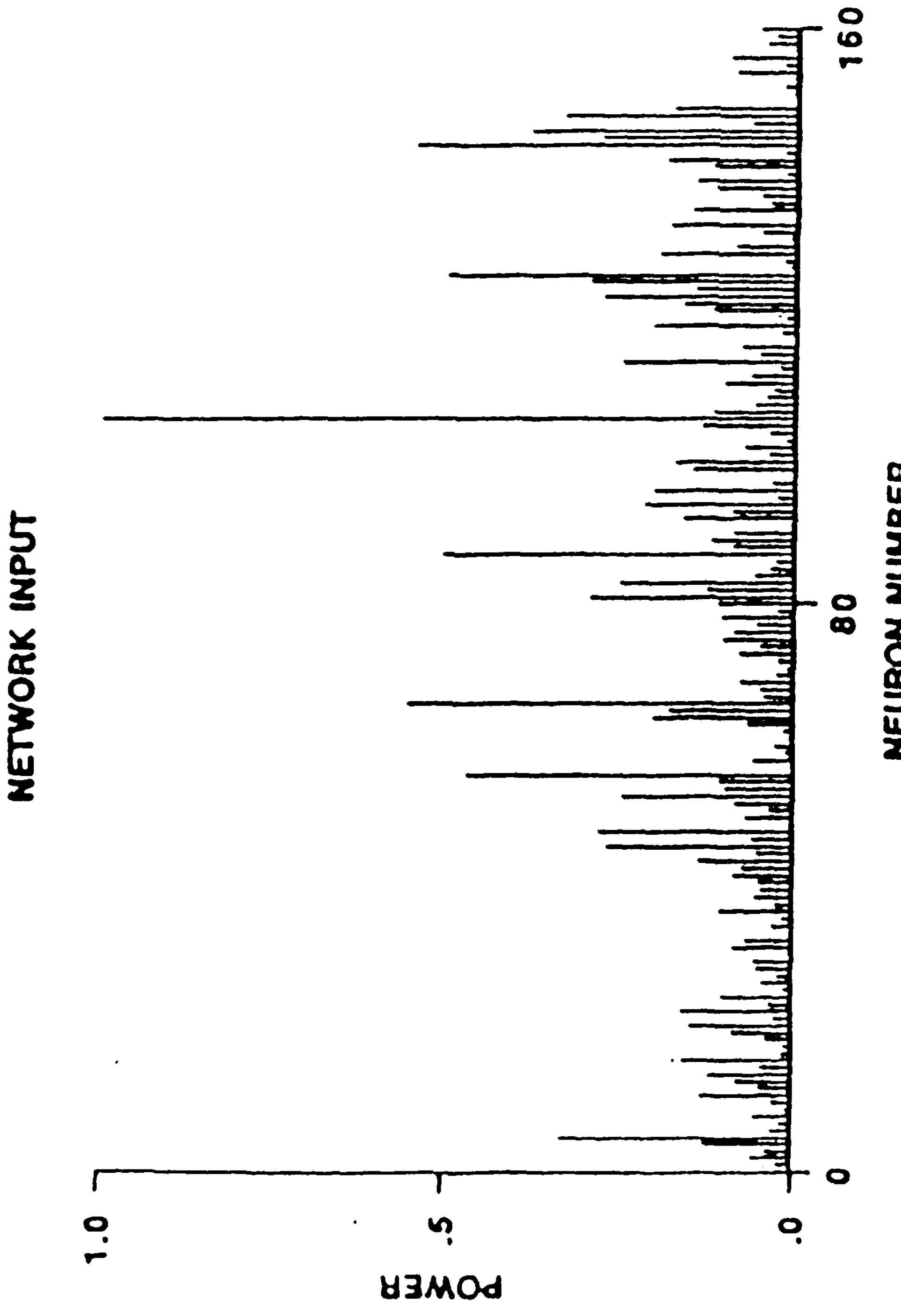

FIGURE 4. NORMALIZED RADAR PATTERN

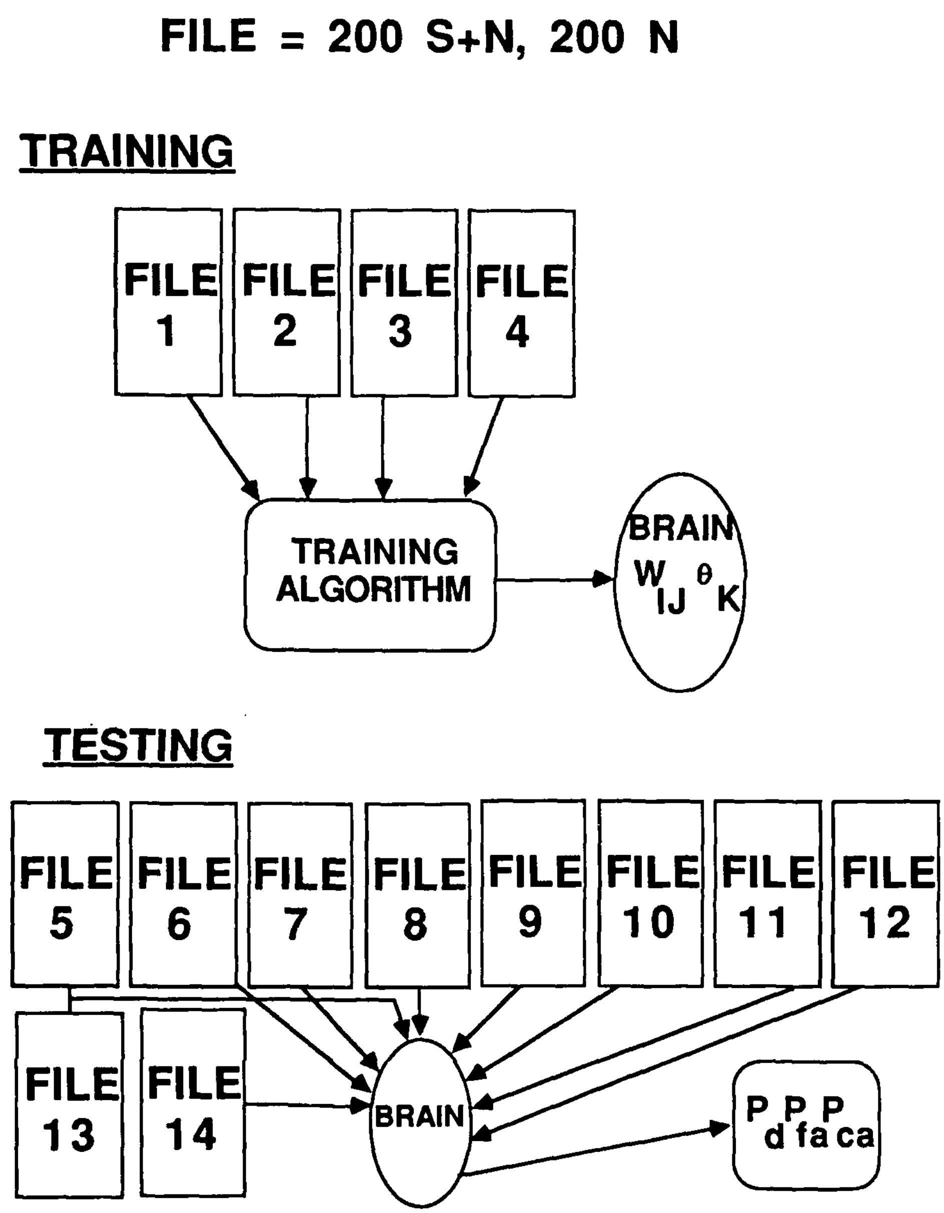

FIGURE 5. NETWORK TRAINING/TESTING

RESULTS

Networks with two, one, and no hidden layers were tested on the data. A typical network architecture of 160 input nodes, 8 hidden nodes in the first hidden layer, 4 hidden nodes in the second hidden lyer, and 2 output nodes is shown in Figure 6. Networks were trained to rms error levels of around .1 using a learning rate of .1 with a .9 rate of momentum transference. Networks usually were able to master about 96 percent of the 1600 training patterns. All training and testing was done on a Sun 3/280 with a Weitek floating point accelerator.

Performance of the networks were characterized by p_{fa}, p_d, and p_{ca}. Network response was determined using a threshold τ as follows:

```
if (output of first output neuron) > τ then
   signal + noise is present
else
   noise is present
endif.
```

Using this criterion the correctness of the networks response could be evaluated.

Performance of the networks as a function of architecture was studied extensively using the 3-dB data. P_{ca}s for various networks with 0 and 1 hidden layers are summarized in Table 1. P_{fa}s and P_ds for the same networks are summarized in Table 2. Results for those networks trained using exponential decay were virtually identical to the results obtained using straight back propagation.

CONCLUSIONS

The highest p_{ca} was obtained by a network with no hidden layer using a threshold value of .5. This seems to indicate that the additional hidden layer in the other networks was trained in an ineffective manner. This problem could be caused by an insufficient number of training examples to converge the edge weights, loss of some of the signals salient feature through use of the normalization procedure, sensitivity of edge weight convergence to initialization, or failure to use small enough learning rates in training.

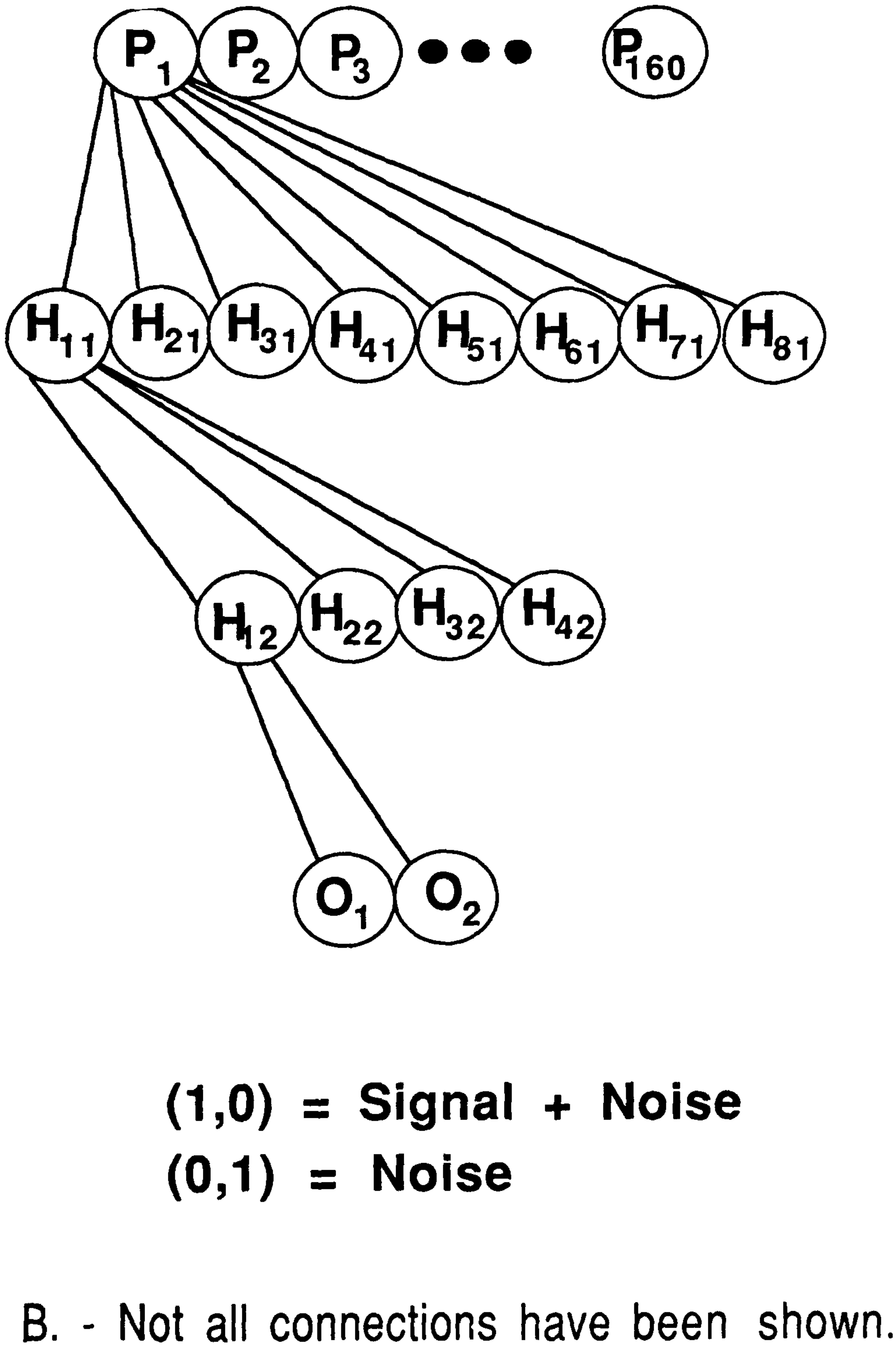

FIGURE 6. SAMPLE NETWORK ARCHITECTURE

TABLE 1. P_{ca} ON 3-dB DATA FOR NO/SINGLE HIDDEN LAYER PERCEPTRONS

Number of Hidden	τ (Threshold)	Selective Learning	PCA (Probability of Correct Answer)
0	.5	no	.9482
6	.5	no	.9360
12	.5	no	.9362
24	.5	no	.9367
0	.9	no	.8462
6	.9	no	.9350
12	.9	no	.9320
24	.9	no	.9282
0	.5	yes	.9475
6	.5	yes	.9365
12	.5	yes	.9475
24	.5	yes	.9452
0	.9	yes	.7815
6	.9	yes	.9045
12	.9	yes	.9320
24	.9	yes	.9005

TABLE 2. P_{fa}, P_d ON 3-dB DATA FOR NO/SINGLE HIDDEN LAYER PERCEPTRONS

Number of Hidden	τ (Threshold)	Selective Learning	PFA (Probability of False Alarm)	PD (Probability of Detection)
0	.5	no	.0380	.9345
6	.5	no	.0700	.9420
12	.5	no	.0600	.9325
24	.5	no	.0565	.9300
0	.9	no	.0040	.6965
6	.9	no	.0450	.9150
12	.9	no	.0330	.8970
24	.9	no	.0305	.8870
0	.5	yes	.0350	.9300
6	.5	yes	.0730	.9460
12	.5	yes	.0400	.9350
24	.5	yes	.0480	.9385
0	.9	yes	.0015	.5645
6	.9	yes	.0185	.8275
12	.9	yes	.0330	.8970
24	.9	yes	.0080	.8090

Alternate criterion for the selection of the "best" network use the p_{fa} and p_d factors. If we require that the network have a p_{fa} less than .01 and a p_d as large as possible then the network with 24 hidden nodes which was trained using selective learning and tested with a threshold of .9 is the best one. The network with no hidden layer which was trained using selective learning and tested with a threshold of .9 is the best network if lowest p_{fa} is the only requirement. This network's low p_{fa} is offset by the fact that it thinks half of the signal plus noise examples are pure noise.

Some ideas to achieve improved edge weight utilization are as follows:

1. single pulse networks with voting,
2. voting with multi-architecture networks,
3. nonlinear normalization procedures,
4. network training with I Q pairs after FFT, and
5. network training with I Q pairs before FFT.

Some preliminary work has been done on these ideas but further work is needed to fully evaluate their potential. Along with evaluating these ideas future work will focus on target detection in clutter.

GLOSSARY

rms = root mean square error for all the output nodes over all the patterns for a given pass

mfac = user supplied control parameter used in selected learning

efac = user supplied scaling factor used in selective learning

I_{ij}, Q_{ij} = I, Q pair associated with the ith range bin on the jth pulse

$\bar{p}_i$ = average power value for the ith range bin over all the pulses

$\bar{p}_{max}$ = maximum of all the p_is over all the bins

sndb = signal to noise ratio in decibels

sn = signal to noise ratio in volts

σ_{tar} = rms for target signal

σ_{noise} = rms for noise

P_{fa} = probability of false alarm, the probability that a network incorrectly identifies a noise return as target

P_d = probability of detection, the probability that a network correctly identifies a target return

P_{ca} = probability of correct answer, the probability that a network correctly identifies a return

τ = threshold on the first output neuron which determines classification

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2. D. E. Rumelhart, G. E. Hinton, and R. J. Williams. 1986. "Learning Internal Representations by Error Propagation." In *Parallel Distributed Processing*, Vol. 1, by D. E. Rumelhart and J. L. McClelland (eds.): 318-62. MIT Press.

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